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Insights to the water balance of a Boreal watershed using a SWAT model

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Abstract

The hydrological characteristics of a watershed play a crucial role in shaping ecosystems within the Boreal zone and have a significant impact on regional environments. Knowing these characteristics, such as the distinctive topography, vegetation, soil composition, and climatic conditions in the Canadian Boreal ecozone, is essential for implementing sustainable water management. This study focuses on assessing the hydrological dynamics of the Upper Humber River Watershed (UHRW) in western Newfoundland, Canada, using the Soil and Water Assessment Tool (SWAT) model. The UHRW includes sub-basins and hydrological response units (HRUs), with diverse land uses, soil types, and slope characteristics. Key parameters influencing streamflow simulation were identified through sensitivity analysis, including the runoff curve number, the effective hydraulic conductivity, the temperature lapse rate, the soil evaporation compensation factor, and the available water capacity of the soil layer. The SWAT model, using data from the Reidville hydrometric station, shows favorable performance metrics, with R^2 values of 0.79 and 0.83 during the calibration and evaluation periods, respectively. The model effectively captures seasonal and monthly flow patterns, displaying right-skewed distributions and seasonal variations. The analyzed hydrological parameters, such as precipitation, evaporation, transpiration, surface runoff, and groundwater flow, reveal their significant contributions to the water balance. The flow duration curve analysis indicates the model's capability to estimate peak and low flows, with slight under-prediction during the recession phase. Seasonal analysis further supports the model's performance, with positive Nash-Sutcliffe Efficiency (NSE) values ranging from 0.65 to 0.91. The study concludes that the SWAT model is suitable for simulating the hydrological processes in the studied watershed providing valuable insights for sustainable water resource management and decision-making in the UHRW. The results can be useful for other Boreal ecozone watersheds.

1. Introduction

Concerns have grown over how environmental changes may affect boreal ecosystems (Brandt *et al* 2013, Shrestha *et al* 2017, Wells *et al* 2020). Variations in hydrological processes, such as streamflow volume (Bera and Maiti 2021), soil moisture (Zare *et al* 2022a), evapotranspiration (Tan *et al* 2019), temperature, runoff magnitude and timing (Brighenti *et al* 2019), and the severity and frequency of floods (Philip *et al* 2019), will in turn affect plant growth and sediment loads (Gassman *et al* 2014) and have greater effects on water resources (Akoko *et al* 2021). Climate change is expected to impact hydrological processes and potentially lead to excess water due to heavy rainfall (Samimi *et al* 2020), or to water scarcity due to lack of rainfall or excessive human consumption and industrial activities (Behera and Devi 2022), and rising water demand (Muhammad *et al* 2020). Variations in the supply and demand of water may also threaten the food security of global communities (Nechifor and Winning 2018). To address upcoming challenges in watershed water management, it is crucial to conduct a local assessment of the hydrological cycle (Raihan *et al* 2020, Fujita *et al* 2022).

Temperature variations owing to climate change are another complication of regional and local water resource management in North America. Long- and short-term impacts can be assessed across nearly every sector of the economy (Baehre *et al* 2011). This is especially true for northern geographical areas, such as Newfoundland and Labrador (NL) in Canada. This area has already experienced significant impacts of climate change on hydrology (Shrestha *et al* 2017, King *et al* 2018, Unc *et al* 2022), primarily in the form of coastal flooding caused by exceptionally heavy rainfall and runoff from the hurricane season, which have altered the streamflow (Hassan 2020). Changes in the quality or quantity of water make remote communities more vulnerable, making it challenging to allocate water to local industries, such as agriculture and energy. Similarly, environmental changes and decreases in water quality have put pressure on the NL fisheries and agriculture sectors, endangering biodiversity and subsistence (MIR 2018). However, excessive and uneven precipitation makes agriculture difficult in western Newfoundland (AAFC 2020).

The Upper Humber River Watershed (UHRW) is of great importance for preserving the ecological well-being and economic stability of western Newfoundland, as noted by Baehre *et al* (2011). The watershed remains largely unspoiled, and its water flow remains unhindered (Jasim 2014). Owing to the favorable climate and soil, many agricultural farms are located in this watershed area (Baehre *et al* 2011). Agriculture is mainly rainfed in western Newfoundland (FFA 2022). In addition to the direct effects of climate change, direct human influences also affect watershed features. These changes include the impact of land conversion on soil hydrology (Altdorff *et al* 2017) and the diversion of water for hydroelectric power generation (Chowdhury 2019). Creating a watershed management assessment and review system for the Upper Humber Basin is necessary to understand the effects of climate change and human influence, including water demand management.

Various hydrological models are available to predict how watersheds respond to changes in precipitation and land use. The Soil and Water Assessment Tool (SWAT) has been found to be especially effective compared to other popular models such as MIKE—SHE, HEC—HMS, TOPMODEL, and WaSiM—ETH (Devia *et al* 2015, Liu *et al* 2016, Chathuranika *et al* 2022). The SWAT model was developed by the Agricultural Research Service of the US Department of Agriculture (USDA-ARS) and Texas A&M AgriLife Research, part of the Texas A&M University System is effective in simulating hydrology in complex watersheds (Arnold *et al* 2012a), as it considers essential factors, such as climate, soil, and land use. SWAT is also open access, meaning anyone can use it for free and efficiently, meaning it can handle large amounts of information without slowing down (Arnold *et al* 2012b). These features make SWAT an excellent choice for understanding complex interactions in watersheds, predicting hydrological components, and determining how they will change over time (Fujita *et al* 2022).

The review of existing research underscores the multifaceted challenges stemming from the intricate interplay between environmental shifts, hydrological dynamics, and historical climatic fluctuations, particularly within the complex context of boreal ecosystems, which are crucial considerations in both water resources planning and flood management (Ireson *et al* 2015, Schuch *et al* 2017, McMillan 2020). The substantial body of research in this field has not yet closed the noticeable research gap in water resources management within watersheds, emphasizing the urgent need for comprehensive and immediate efforts to address it. To address this gap, it is crucial to conduct a thorough, location-specific assessment of hydrological processes within specific watersheds (McMillan 2020), such as the UHRW in NL, Canada. However, the importance of addressing this gap in research cannot be overlooked. The vulnerability of NL's agriculture, along with its remote communities, is intrinsically intertwined with the stability and quality of its water resources.

Moreover, the specific climatic and geographical aspects of the boreal ecosystem in the UHRW require a tailored approach to sustainable water resource management. By scrutinizing localized hydrological processes and their potential transformations, a deeper understanding of the conditions leading to the sustainability of the whole socio-ecological system depending on the watershed can be gained (Beven 2019). Therefore, this study aims to bridge this gap by crafting a hydrological model grounded in the SWAT framework, which was meticulously calibrated for the UHRW. This endeavor seeks to holistically simulate the water balance constituents and the hydrological processes unique to the boreal region. By addressing this information deficit and by building a robust foundation for understanding and predicting hydrological dynamics in the UHRW, this study provides essential insights to enhance sustainable water management. Ultimately, this effort reinforces the resilience of both the ecosystems and the communities reliant on these vital resources, emphasizing the importance of comprehensive hydrological studies for sustainable development in vulnerable regions.

2. Methodology

2.1. Study area

The Humber River watershed is located near the west coast of Newfoundland Island. The headwaters begin in the Gros Morne National Park and flow 153 km before reaching the Bay of Islands in Corner Brook (ECC 2023a). With a total basin area of 7,860 km^2, the Humber River is the second largest river basin on the

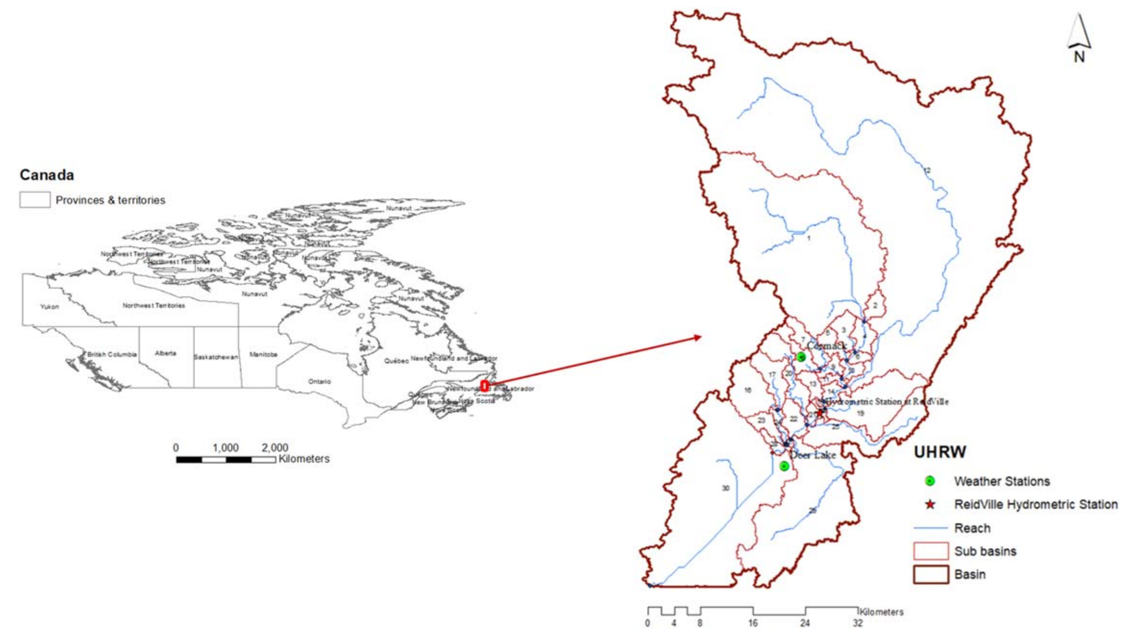

Figure 1. Upper Humber River Watershed, UHRW (2,890.59 Km^2) in Western Newfoundland, Canada, and locations of weather stations, and the hydrometric station at Reidville used for the Upper Humber River data collection (Hydrometric ID 02YL001).

island. Its two main branches are the Upper Humber River (2,110 km^2) and the 5,000 km^2 Grand Lake (ECC 2023b). The Upper Humber River basin has not yet been developed. However, the flow in the Grand Lake Basin is regulated for hydroelectricity generation and is home to two major and several smaller lakes. Figure 1 illustrates the location of the UHRW.

2.2. SWAT model description

The SWAT model simulates hydrological variables such as streamflow at a watershed scale on a daily, monthly, and annual time frame, continuous time, and spatial distribution (Arnold *et al* 2012a). It uses hydrologic response units (HRUs) to represent areas that can be lumped together as homogeneous and comprising certain features of the slope, soil, and land use. Within a watershed, geographical variability in terms of slope class, soil type, and land cover is described for each HRU. For each HRU, the model calculated the relevant hydrological elements, including surface runoff, groundwater flow, evapotranspiration, and sediment output. A GIS interface has an embedded SWAT, which is a graphical user interface for the SWAT model and is now a desktop ArcMap extension (Frankenberger and Daneshvar 2019).

The SWAT model simulates the hydrological components of the UHRW based on the water balance equation (1) (Neitsch *et al* 2011).

$$SW_t = SW_o + \sum_{i=0}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - W_{gw}) \tag{1}$$

where SW_t is the final water content (mm), SW_o is the initial water content of the soil, t is the stated time in days, R_{day} is the amount of precipitation in a day expressed as R_{day} (mm), Q_{surf} is the runoff amount on a particular day i (mm), E_a is the evapotranspiration amount on day i (mm), W_{seep} is the amount of water percolated into the vadose zones on day i (mm), and W_{gw} is the return amount of flow on day i (mm).

In this study, the Natural Resources Conservation Service (NRCS), formerly the Soil Conservation Services (SCS) curve number (CN) method (Mishra and Singh 2003) was used in the SWAT model to estimate the surface runoff of the UHRW. The Penman-Monteith method (Howell and Evett 2017) was used to estimate potential evapotranspiration (PET), and the actual evapotranspiration was calculated (Allen *et al* 1998). SCS—CN is described by the following equation (2):

$$Q_{sro} = \frac{(PR_d - 0.2S)^2}{(PR_d - 0.8S)^2} \tag{2}$$

where Q_{sro} is the depth of runoff (mm), and PR_d is the depth of daily precipitation (mm). S is the maximum potential retention parameter in millimeters and can be determined using equation (3):

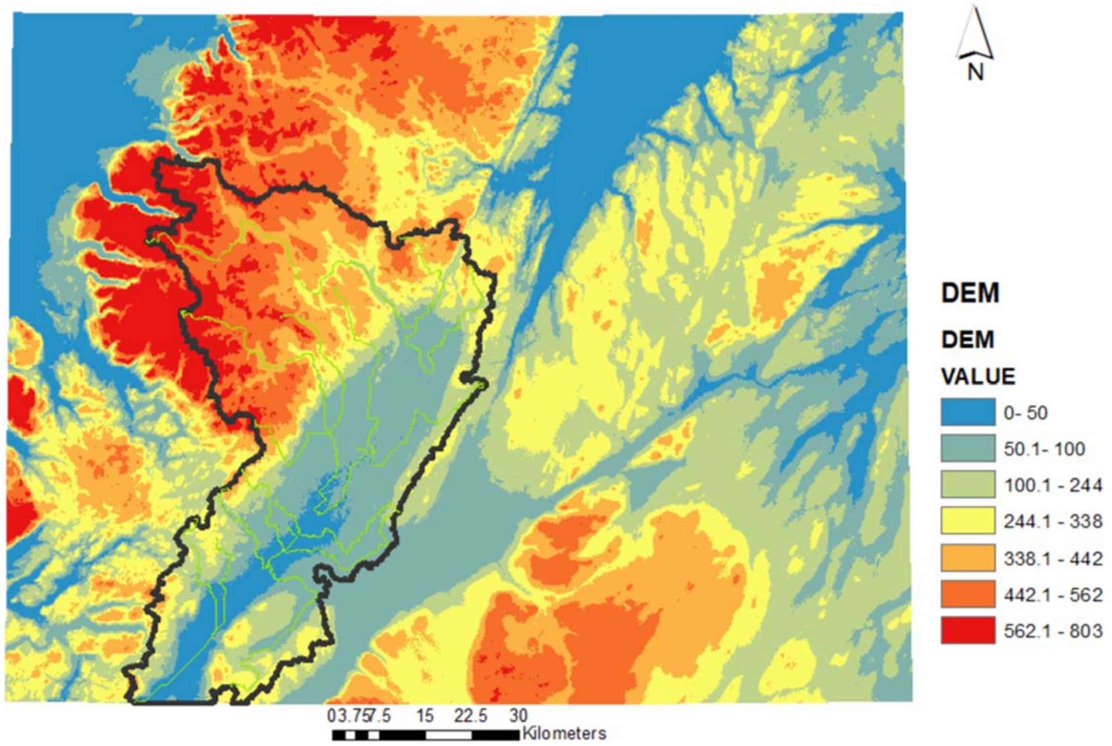

Figure 2. Digital Elevation Model of the study area.

$$S = 254\left(\frac{100}{CN} - 1\right) \tag{3}$$

Where *CN* is the curve number, which has a range of $100 \geqslant CN \geqslant 0$, where a higher CN value represents low potential retention, and a $CN = 0$ value indicates that the retention is $S = \infty$. CN depends on the permeability of the soil, infiltration, land use, and soil-water conditions (Singh and Saravanan 2020).

2.3. Model input

To accurately use the SWAT model, a comprehensive database that includes information on topography, soil, land use, and meteorological and hydrological conditions must be developed using inputs such as the Digital Elevation Model (DEM), soil data, and climate data through the ArcSWAT interface (Arnold *et al* 2012b). To ensure the best possible results, river discharge and climate data were used during the calibration and evaluation phases of the SWAT model (as described below). The accuracy of the SWAT model predictions is determined by the extent to which the input variables reflect the unique characteristics of the watershed (Daggupati *et al* 2018).

2.3.1. DEM

After the SWAT project, the DEM was the first input raster file for developing the hydrological model. The DEM is a raster data file that provides elevation information (Zhang *et al* 2014). SWAT created a watershed delineated using the DEM. This specific type of data, that is, raster data, consists of an array of pixels containing elevation information (Buakhao and Kangrang 2016). DEM was used to determine the topography, which describes the height of different points in an area, to find river stream networks and sub-basins, and to calculate slopes for HRUs (Reddy and Reddy 2015). In this study, DEM was collected from the Canadian Digital Elevation Model at a resolution of 20 m × 20 m. The DEM was downloaded from the Canadian government website (https://open.canada.ca/en) and projected onto the WGS1984 UTM Zone 21 N coordinate system in desktop ArcMap. The DEM was processed using a GIS environment, specifically, the ArcGIS interface and watershed delineator (figure 2).

2.3.2. Soil data

The Soil and Landscapes of Canada (SLC) database contains information on soil types, version 3.2, explicitly focusing on data for Canada's major agricultural regions at provincial and federal levels (Amichev *et al* 2015, SLC A 2021). This database contains data on 11,838 different soil records (Cordeiro *et al* 2018), and is a GIS layer that can contain multiple soil records within a single polygon. The SLC database focuses primarily on agricultural

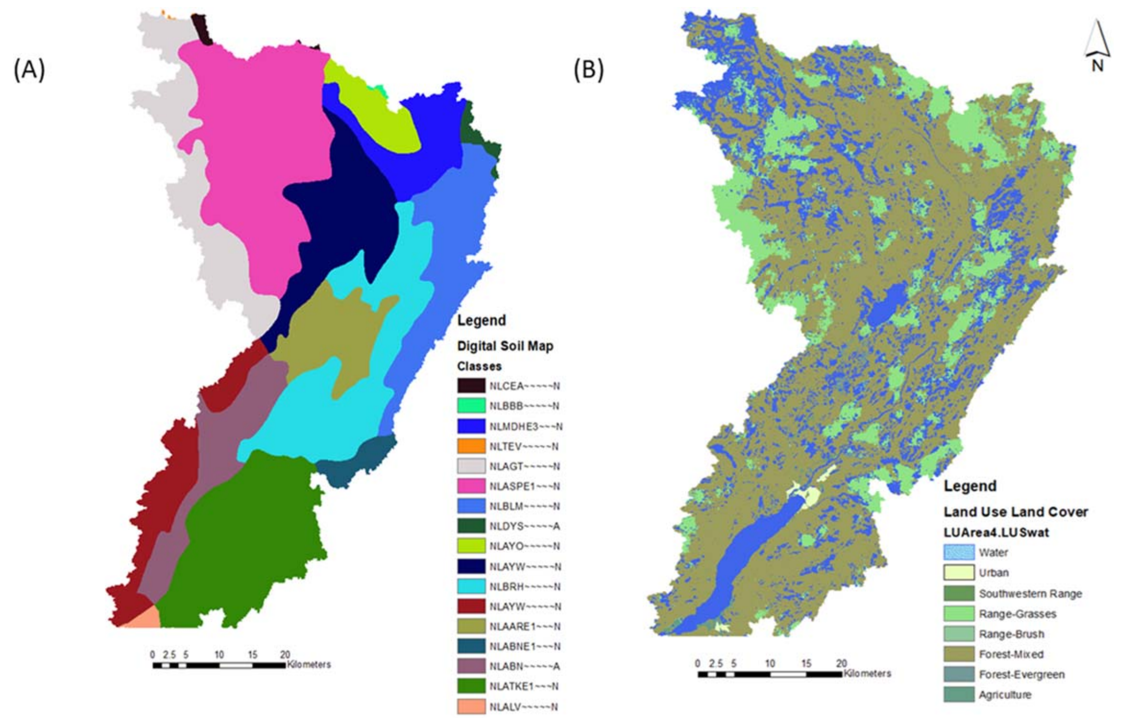

Figure 3. Spatial distribution of SWAT input data for the UHRW with digital soil class (A) and land use and land cover class (B).

areas and is a vital resource for the SWAT simulation model (Cordeiro *et al* 2018). In this study area, 17 different soil types were identified, with loam soil covering most of the watershed, accounting for approximately 27% of the entire region. Overall, the impact of surface runoff over the watershed was primarily influenced by finer-resolution SLC soil classification.

2.3.3. Weather data

Incorporated into the SWAT model were weather data sourced from historical records, encompassing daily precipitation and both maximum and minimum temperatures, obtained from the Environment and Climate Change Canada's historical weather data repository, accessible at https://climate.weather.gc.ca/historical_data. Furthermore, to enhance the model's comprehensiveness, the WGEN model was employed to generate crucial meteorological variables, including relative humidity, wind speed, and solar radiation.

Our dataset was meticulously compiled from two distinct weather stations, namely Cormack RCS and Deer Lake, spanning the extensive time frame from 1982 to 2022. This comprehensive dataset encompassed a total of 30,681 data points. Nevertheless, it is essential to note that our dataset was not without its challenges, as it contained 1,084 missing values, constituting approximately 3.5% of the total data points. To address this challenge, in line with the guidelines outlined in the SWAT manual (Neitsch *et al* 2011), we employed a placeholder value of −99.0 to estimate and fill in these missing data points, ensuring the completeness and integrity of our dataset for subsequent analyses and modeling efforts.

2.3.4. Land use and land cover

Land Use and Land Cover (LULC) is a crucial factor in a physically based hydrological model (Dwarakish and Ganasri 2015) as it affects the runoff, evapotranspiration, and soil erosion in a catchment (Getu Engida *et al* 2021). The 2022 LULC map was extracted from the Environmental Systems Research Institute (ESRI) at a resolution of 10 m (Esri 2023). The LULC raster image was derived from the European Space Agency (ESA) Sentinel-2 imagery (Esri 2023). Eight land cover classes were identified and reclassified to align with the SWAT crop growth, LULC, and database. These classes include forest (mixed), rangeland, forest-evergreen, agricultural land, range-brush, urban, southwestern range, and water bodies. The LULC in the study area was reclassified using an unsupervised classification method at the ArcSWAT interface (figure 3). The incorporation of the AI-driven LULC classification resulted in significant changes within the realm of hydrological modeling and prediction.

Table 1. Input data used in the SWAT model.

Data	Type	Source
Canadian Digital Elevation Model	Raster, resolution –20 m	http://geogratis.gc.ca accessed on February 2023
Land use	Raster, resolution – 10 m	https://www.esri.com/ accessed on March 2023
Soil type	Vector	http://www.agr.gc.ca accessed on January 2023
Streamflow	Daily	https://wateroffice.ec.gc.ca accessed on March 2023
Climate	Daily	https://climate-scenarios.canada.ca accessed on April 2023

Table 2. Percentage of total basin area dedicated to land use.

LULC class	LULC category	Area (ha)	Area coverage (%)
FRST	Forest-Mixed	179,430.3575	61.88
WATR	Water	63,077.1009	21.75
RNGE	Range-Grasses	44,128.1137	15.22
FRSE	Forest-Evergreen	876.7782	0.30
AGRL	Agricultural Land	1,880.6807	0.65
RNGB	Range-Brush	546.7917	0.19
URBN	Residential	26.1842	0.01
SWRN	Southwestern Range	1.7674	0.001

2.3.5. River discharge

Humber River discharge data are crucial for calibrating and validating the model in the research area. Discharge measurements were gathered at the Reidville hydrometric station located along the Humber River within the basin (figure 1). The Reidville hydrometric station data were used to calibrate and validate the model. The calibrated model can then predict the river discharge in the study area. Daily river discharge data were obtained from the Environment and Natural Resources, Canada (https://wateroffice.ec.gc.ca/), from 1982 to 2022. Table 1 provides a summary of the data sources employed in our hydrological modeling, which were interfaced with ArcSWAT.

2.4. Model set-up

The SWAT model research project was established using the ArcSWAT2012 interface in ArcMap 10.7. This GIS interface enabled the SWAT model to automatically perform stream reach parametrization, watershed delineation, and sub-basin geomorphology. The flow direction and accumulation were determined using a stream definition based on a DEM (Neitsch *et al* 2011). The model outlined 30 sub-basins with drainage requirements of 1,000 ha (or 10 km^2) and a single exit point for each watershed. The LULC and soil data were inserted, reclassified, and combined with slope class information. The HRUs were defined by combining 10% of the land use area, 15% of the soil class, and 15% of the slope class over the sub-basin, land use, and soil area, respectively, resulting in 251 HRUs. After importing the climate data set, additional inputs were used to run the SWAT model. These input files were organized and modified to meet the research requirements and objectives. Finally, the SWAT model was used to simulate the various hydrological components. The flowchart (figure 4) shows the overall SWAT modeling process.

2.4.1. Watershed characteristics

The watershed was divided into 30 sub-basins and 251 HRUs, which were classified based on the soil type, land cover, land use, and slope. The average CN of the watershed was 71.54, with a higher CN indicating greater potential for surface runoff. This is determined by factors, such as land use, soil hydrological conditions, hydrologic soil groups, and residual moisture conditions. The elevation of the basin ranges from 3 to 781 m, and the dominant land use and soil types are Forest-Mixed and Loam, respectively (tables 2, 3). The majority of the watershed (89%) has a medium-to-high slope (3% and above) (table 4).

2.4.2. Parameterization

The SWAT model includes many parameters that represent hydrological processes, and choosing the appropriate parameters can be difficult because of the conditional nature of the fitting of parameters to the objective functions (Arnold *et al* 2012a). Though measurements of physical systems have limited application, the SWAT Calibration and Uncertainty Program (SWAT-CUP) was used in this study to perform sensitivity

Table 3. Soil types and coverage within the basin.

Soil class	Soil category	Area (ha)	Area coverage (%)
NLASPE1~~~N	Loam	54,897.48	18.93
NLATKE1~~~N	Sandy loam	40,327.86	13.91
NLBRH~~~~~N	Loam	35,510.56	12.25
NLAYW~~~~~N	Silt loam	26,436.29	9.12
NLAGT~~~~~N	Clay loam	25,238.76	8.7
NLBLM~~~~~N	Clay loam	24,886.38	8.58
NLABN~~~~~A	Loam	18,306.62	6.31
NLAYW~~~~~N	Clay loam	17,133.11	5.91
NLAARE1~~~N	Sandy loam	16,111.07	5.56
NLMDHE3~~~N	Sandy	1,5,040.27	5.19
NLAYO~~~~~N	Clay loam	7947.62	2.74
NLABNE1~~~N	Sandy loam	4,033.93	1.39
NLDYS~~~~~A	Clay loam	1,888.60	0.65
NLALV~~~~~N	Silt loam	1,060.46	0.37
NLCEA~~~~~N	Silty clay loam	867.41	0.3
NLBBB~~~~~N	Loamy sand	215.23	0.07
NLTEV~~~~~N	Sandy loam	66.0497	0.02

Table 4. Distribution of slope classes and coverage in the watershed.

Slope class limit (%)	Area (ha)	Area coverage (%)
0–3	30,772.27	10.6
3–10	103,496.03	35.7
10–9999	155,699.48	53.7

analysis, calibration, evaluation, and uncertainty analysis of the SWAT model (Abbaspour *et al* 2018). The SWAT-CUP allows the creation of an envelope of reasonable solutions by performing parameter sampling, accounting for the goodness of fit and uncertainties in the conceptual model (Abbaspour *et al* 2004). The regional calibration of the parameters is possible, providing greater freedom in selecting the distributed parameter scheme.

The streamflow parameters were regionalized into upper, middle, and lower sections based on drainage areas and streamflow station locations to account for these variations. To modify the parameters for each section, ranges were selected based on the local applications performed for the UHRW. This approach ensured that the initial amplitudes of the modified parameters were physically meaningful and compatible with those of the study area. The SWAT-CUP program was used to perform sensitivity analysis to evaluate the impact of each parameter on the model output. This analysis identified the most sensitive parameters for each section of the UHRW that were then used for calibration and evaluation. In this study, 15 parameters were used to simulate the monthly streamflow, after a comprehensive literature review. The primary variables reflected by these parameters are soil, runoff, and channels.

2.4.3. Model calibration

In this study, we used SUFI-2, a model calibration technique, to improve the single simulations through multiple iterations based on the objective function (Yang *et al* 2008, Abbaspour 2015). However, our study required only up to four iterations, with 500 simulations conducted during one iteration for the UHRW calibration. Our model's simulations covered the period January 1, 1982, to December 31, 2022, with a monthly time step. The first three years of the simulation (1982–1984) were considered the warm-up period to ensure that the model reached a quasi-steady-state condition. Calibration was performed for the period 1984–2010 and the evaluation was conducted over the last 11 years (2011–2022). During the evaluation, we used the parameters determined during the calibration process and compared the model's predictions with the observed data that were not used for calibration. We utilized the monthly average streamflow data from the hydrometric station located in Reidville to calibrate and evaluate the model.

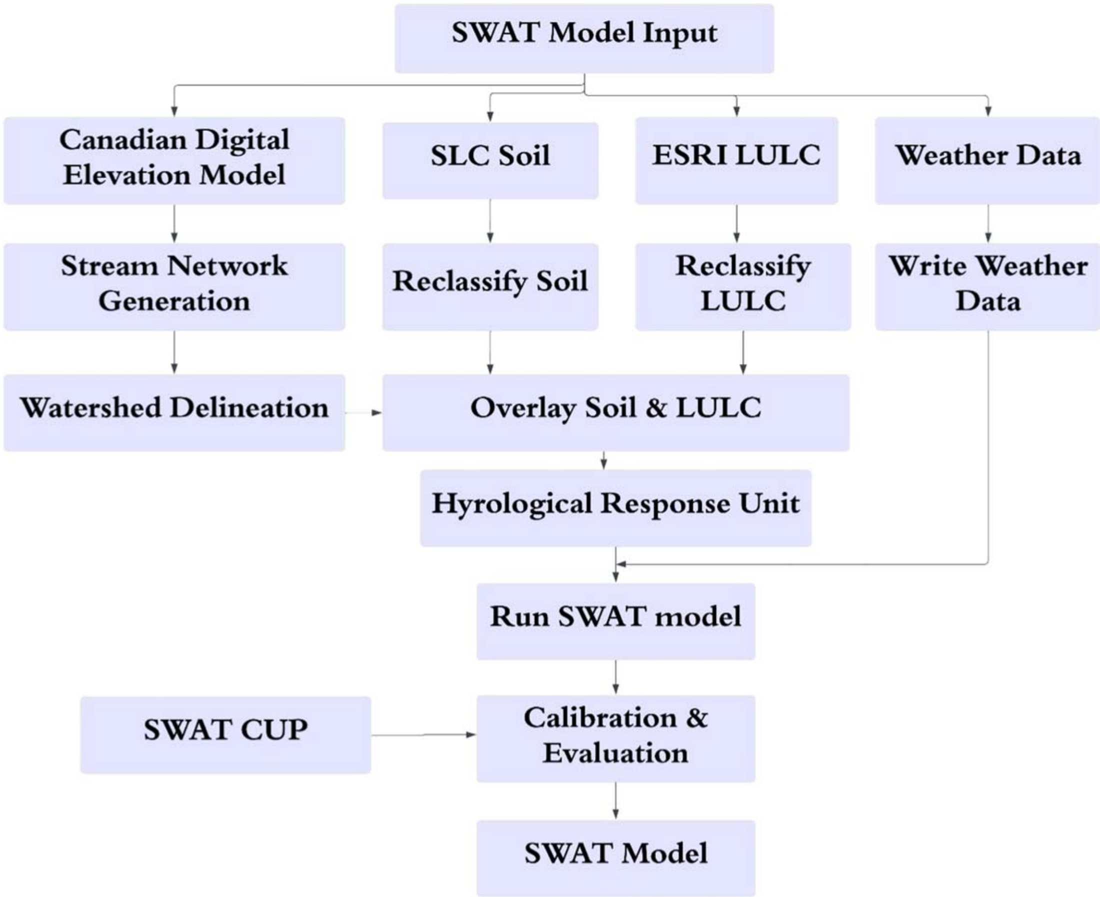

Figure 4. Flowchart of SWAT model setup for Upper Humber River Watershed (UHRW).

2.4.4. Model evaluation statistics

To assess the performance of individual simulations, we conducted a statistical analysis to gauge the strength of the linear relationship between the observed and simulated data. To evaluate the performance of the model, we employed the various statistical metrics recommended by Moriasi *et al* (2007) and Krause *et al* (2005). These metrics encompassed the coefficient of determination (R^2), the Nash-Sutcliffe Efficiency (NSE), the root mean square error (RMSE), the percentage bias (PBIAS), and the standard observation ratio (RSR). In this study, we adopted the NSE as the primary objective function. A value falling within the range of 0.5–0.75 was deemed as indicative of good performance, while values surpassing 0.75 were considered highly favorable outcomes (Aawar and Khare 2020). Additionally, it was advised to evaluate absolute or volume errors along with the efficiency criteria to ensure the reliability of the model, as recommended by Krysanova and White (2015).

The second statistical metric employed was RSR, which quantifies the ratio of the RMSE to the standard deviation (SD) of the observations. This standardization of the RMSE provides insight into the dispersion of the residuals (McMillan *et al* 2016). Finally, the PBIAS was utilized to gauge the average tendency of the simulated data to either surpass or fall short of their corresponding observations. A PBIAS value of 0 represents the optimal scenario, where positive values indicate an underestimation bias and negative values denote an overestimation bias in the model (Waseem *et al* 2017). For reference, the equations for calculating the R^2, the NSE, the RMSE, and the PBIAS bias are discussed in what follows:

2.4.4.1. Coefficient of determination (R^2)

R^2 is a measure of the proportion of the total variability in the observed data that is explained by the model (Saunders *et al* 2012). The R^2 values range from 0 to 1. A value closer to one indicates that a larger proportion of the variability in the dependent variable is explained by the independent variables, suggesting a better fit of the model to the data (equation 4). However, a value closer to zero suggests that the model does not explain much of the variability, indicating a poor fit (Rashid 2014).

$$R^2 = \frac{\sum_{i=1}^{t}(X_i - \bar{\bar{X}})(Y_i - \bar{\bar{Y}})}{\sqrt{\sum_{i=1}^{t}(X_i - \bar{\bar{X}})^2(Y_i - \bar{\bar{Y}})^2}} \tag{4}$$

where X_i and Y_i are the observed and the predicted values, respectively, for streamflow $\bar{X}$ is the mean of the measured streamflow, $\bar{Y}$ is the mean of the model-predicted streamflow, and t is the total number of simulation periods.

2.4.4.2. Nash–sutcliffe efficiency (NSE)
NSE is a measure of the predictive accuracy of the model (Nash and Sutcliffe 1970). NSE is a valuable tool for gauging the effectiveness of models. Values exceeding 0.75 are considered highly favorable, demonstrating a strong agreement between the predictions and observations. NSE values between 0.5 and 0.75 also indicate good performance, suggesting a reasonable alignment between the model and the data (equation 5). Using NSE as a metric, researchers and practitioners can quantitatively assess how well their models capture real-world patterns and behaviors (Yesuf *et al* 2016).

$$NSE = 1 - \frac{\sum_{i=1}^{t}(X_i - Y_i)^2}{\sum_{i=1}^{t}(X_i - \bar{X})^2} \tag{5}$$

2.4.4.3. Percent bias (PBIAS)
PBIAS is a measure of the average tendency of the model to either overestimate or underestimate the observed streamflow values. PBIAS calculates the average percentage by which a model's predictions deviate from observed values. The optimal PBIAS value is 0, indicating that the model accurately predicted observations without bias. Positive PBIAS values indicate an underestimation bias, implying that the model consistently predicted lower values than those observed. Conversely, negative PBIAS values indicate an overestimation bias, suggesting that the model predicts higher values (McMillan *et al* 2016).

$$PBIAS = \frac{\sum_{i=1}^{t}(X_i - Y_i)}{\sum_{i=1}^{t}(X_i)} \times 100 \tag{6}$$

where PBIAS is the ratio in which the symbols from equation (4) are used to express the amount of variation between the measured and predicted streamflow.

2.4.4.4. Root mean square error (RMSE)
RMSE serves as a valuable metric for quantifying the typical difference between the observed and simulated streamflow values. This reflects the square root of the average squared discrepancy between the observed and simulated streamflow data. A smaller RMSE value signifies stronger alignment between the observed and simulated datasets, indicating a closer match between the two (Gupta *et al* 1999).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{t}(X_i - Y_i)^2}{t}} \tag{7}$$

$$RSR = \frac{\sum_{i=1}^{t}(X_i - Y_i)^2}{\sqrt{\sum_{i=1}^{t}(X_i - \bar{X})^2}} \tag{8}$$

The symbols used in the equations are defined in equation (4), all of which are important for evaluating the performance of hydrological models, and each provides information regarding the accuracy and bias of the model. A good model has high R^2 and NSE values and low PBIAS and RMSE values, indicating a strong correlation between the observed and simulated data, little bias, and low error (Moriasi *et al* 2007).

2.4.5. Flow duration curve (FDC) analysis
In addition to evaluating the performance and employing statistical methodologies, the analysis of observed and predicted streamflow measurements encompassed the utilization of flow threshold indices that are widely applied in water resource planning (Daraio 2020). To elucidate the interplay between the flow rate and frequency, researchers harnessed the FDC, a concept in use since 1915 as described in a USGS report (Atkisson 1915, Searcy 1959). The FDC is a graphical representation that captures the cumulative distribution function of flow rates (Vogel and Fennessey 1994). The FDC served as a window for the inherent characteristics of the flow regime. A pronounced FDC steepness signifies a flow regime dominated by rapid fluctuations and prominent storm hydrographs, which is indicative of minimal baseflow. Conversely, a gently sloping FDC

Table 5. Calibration SWAT parameters with fitted values and ranks for the Upper Humber River Watershed model.

Parameter	Type	Description	Initial range	Fitted value	Rank
r_CN2.mgt	R	SCS runoff curve number	−0.2–0.2	0.0996	1
v_CH_K2.rte	V	Effective hydraulic conductivity in main channel alluvium(mm/h)	5.0–130.0	63.625	2
v_TLAPS.sub	V	Temperature lapse rate	−10–10	9.860	3
v_ESCO.hru	V	Soil evaporation compensation factor	0–1	0.913	4
v_EPCO.hru	V	Plant uptake compensation factor	0–1	0.899	5
v_SURLAG.bsn	V	Surface runoff lag time	0.05–24	3.427	6
r_SOL_AWC.sol	R	Available water capacity of the soil layer	−0.2–0.4	−0.089	7
v_SFTMP.bsn	V	Snowfall temperature	−5.0–5.0	4.670	8
v_GWQMN.gw	V	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0–5000	715	9
v_GW_REVAP.gw	V	Groundwater 'revap' coefficient	0.0–0.2	0.081	10
r_SOL_BD.sol	R	Moist bulk density	−0.5–0.6	−0.179	11
r_SOL_K.sol	R	Saturated hydraulic conductivity(mm h^{-1})	−0.8–0.8	0.738	12
GW_DELAY.gw	V	Groundwater delay (days)	0–500	305	13
v_CH_N2.rte	V	Manning's 'n' value for the main channel	0.0–0.3	0.234	14
v_ALPHA_BF.gw	V	Baseflow alpha factor (days)	0–1	0.111	15

indicates a flow regime characterized by sustained groundwater contributions and subdued stormflow responses (Burt and Heathwaite 1996).

2.4.6. Data analysis

The model simulation data underwent analysis using R packages specialized in hydrology, such as HydroTSM developed (by Zambrano-Bigiarini 2022a) for hydrological time series manipulation and HydroGOF (Zambrano-Bigiarini 2022b) for assessing model fit. Data processing was conducted using the tidyverse package (Wickham *et al* 2019), while graphical representation employed the Grammar of Graphics, ggplot2 (Wickham 2016). All data analysis and visualization were done by RStudio: Integrated Development Environment for R (R Core Team 2023 and Posit Team 2023). Furthermore, the project necessitated the processing of various essential data types, including climate, land use, soil, elevation, and measured streamflow, which were crucial for model execution. Throughout the calibration and evaluation phases, these simulation data played a pivotal role in statistical analysis, serving as a fundamental step to ensure the model's precision and reliability.

3. Results and discussion

3.1. Results

3.1.1. Sensitivity of model parameters

The ranges of the initial and fitted values for the selected parameters are listed in table 5. Notably, the utilization of fitted parameters within their designated initial ranges had a substantial impact on the streamflow simulation procedure. The current phase of the study involved the identification of the most influential parameters through a global sensitivity analysis conducted during monthly calibration using the SUFI-2 algorithm, as shown in table 5.

The results of this investigation revealed that the streamflow simulation was predominantly affected by several key model parameters. The parameters were r_CN2.mgt (runoff curve number for the SCS), v_CH_K2.rte (effective hydraulic conductivity in the alluvial areas of the main channel), v_TLAPS.sub (temperature lapse rate), v_ESCO.hru (compensation factor for soil evaporation), and r_SOL_AWC.sol (available water capacity of the soil layer). Conversely, some parameters displayed considerably lower sensitivity compared to the highly influential ones. Changes in the range of these less sensitive parameters had minimal impact on the streamflow simulation process and did not significantly alter the model output.

3.1.2. SWAT model calibration and evaluation

The SWAT model is a commonly used hydrological model that simulates the river basin water balance and quality. The calibration and evaluation of the SWAT model involved adjusting the model parameters to fit the observed data during the calibration period, and then testing the model's performance on independent data during the evaluation period. In this case, the calibration and evaluation of the SWAT model were carried out using Humber River discharge data from the Reidville gauged station. The data were divided into a calibration period from 1984 to 2010, and an evaluation period from 2011 to 2022. The SWAT model was calibrated and

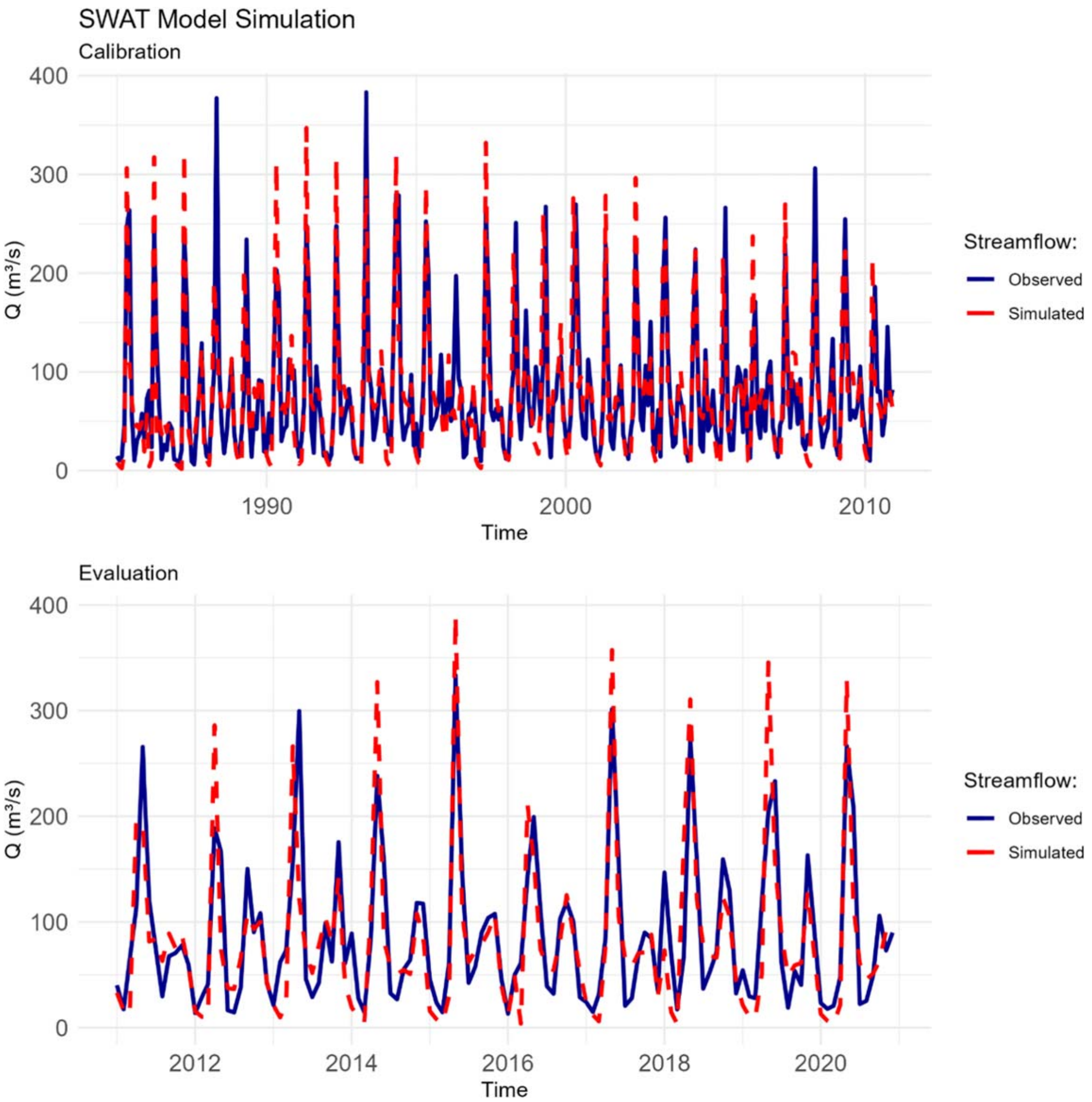

Figure 5. Comparison of simulated and observed monthly discharge of the Upper Humber River at Reidville.

Table 6. Summary of the SWAT model performance for calibration and evaluation periods.

Period	Year	Statistical analysis of model performance					
		p-factor	r-factor	R^2	RSR	PBIAS	NSE
Calibration	1984–2010	0.75	0.69	0.79	0.71	6.9	0.79
Evaluation	2011–2021	0.71	0.56	0.83	0.43	− 8.1	0.82

validated using the SUFI-2 algorithm, which adjusted the model parameters to minimize the difference between the observed and simulated data. Figure 5 depicts the simulated Upper Humber River flow versus the observed monthly river flow.

The model's performance was evaluated using statistical and graphical methods. Figure 5 shows the observed monthly river flow compared with the simulated Upper Humber River flow. The disparities in extremes between observed and simulated flows in figure 5 prompt consideration of climate change effects on weather patterns. As contemporary climate dynamics exhibit heightened frequency and magnitude of extreme events, it is imperative to acknowledge that these changes may contribute to observed discrepancies, enriching the discussion on the model's performance by accounting for the evolving hydrological landscape influenced by climate change. A statistical analysis of model performance during the calibration and evaluation periods is presented in table 6. The p-factor and r-factor are measures of model sensitivity to the input and output data, respectively.

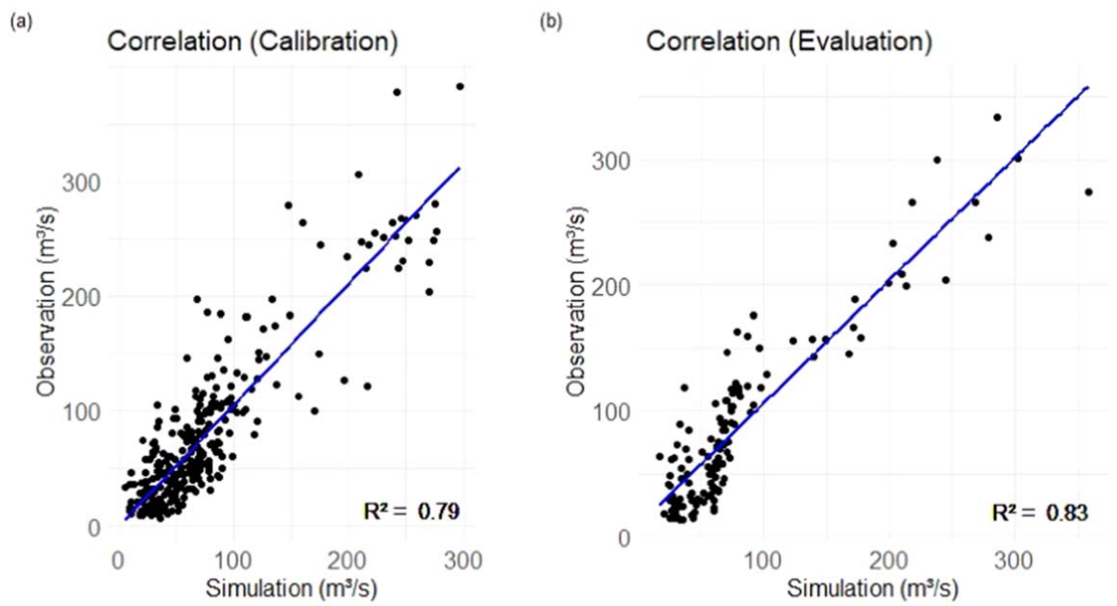

Figure 6. Correlation performance of measured and observed data during (a) calibration and (b) evaluation.

The calibration and evaluation results show that the SWAT model performed well, with R^2 values of 0.79 during the calibration period and 0.83 during the evaluation period. NSE values were also high, indicating good predictive accuracy. The PBIAS values were close to zero, indicating minimal bias in the model predictions. The RSR values were below 1, indicating that the model predictions had a lower variability than the observed data. Despite these positive results as illustrated in figure 6, consistently elevated observed flow data compared to simulated data raises questions, pointing to potential factors such as unaccounted climate variability, alterations in land use patterns, and local-scale influences not fully captured by the model. A thorough exploration of these potential sources of variability and uncertainties is imperative for a comprehensive understanding of the observed differences in flow magnitudes between simulation outputs and actual measurements. This is a fruitful topic for further research, which is beyond the scope of the present analysis.

According to the calibration and evaluation results, the predicted monthly Upper Humber River flow and the actual observed data were in good agreement, as presented in table 6. Moriasi *et al* (2007) indicated that the model calibration and evaluation results have very good performance if the R^2 and NSE values are greater than 0.5, and the PBIAS is within the range of 0% to 15%. As indicated in table 6, the model was confirmed to have effective predictive capability. Therefore, it may be argued that the model is appropriate for the UHRW analysis based on the model's calibration and evaluation parameters selection and results.

3.1.3. Watershed hydrological components

Hydrological processes include precipitation, evaporation, transpiration, interception, surface runoff, and the storage and flow of groundwater, all of which affect the water delivery, storage, and outflow of watersheds. The average precipitation (1,311.4 mm) is higher than that in the north-central region of the island because Newfoundland is situated in a humid continental climatic zone impacted by the north Atlantic Ocean influences, and natural climate variation in Canada has an impact on precipitation (Amponsah *et al* 2019).

The SWAT model was updated to incorporate calibrated values of the model parameters, and the water balance components of the watershed were computed from 1984 to 2022. The water balance components are shown in figure 7. The yearly average values are, for precipitation 1,311.4 mm, for evapotranspiration 295 mm, for surface runoff 372.54 mm, and for percolation 325 mm. The range of surface runoff was 261 mm to 509.34 mm, with the highest value observed in 2018 and the lowest in 2010. Surface runoff fluctuations are caused by rainfall variations. The variables of surface runoff, water yield, groundwater, and percolation all contributed significantly to the water budget in 2018, the wettest year on record. The highest evapotranspiration (ET) value of 344.72 mm was recorded in 2010, while the lowest ET value of 261.66 mm occurred in 1991, and these fluctuations are attributed to the presence of a fully established vegetation canopy and a high descending radiation flux in relation to sufficient precipitation.

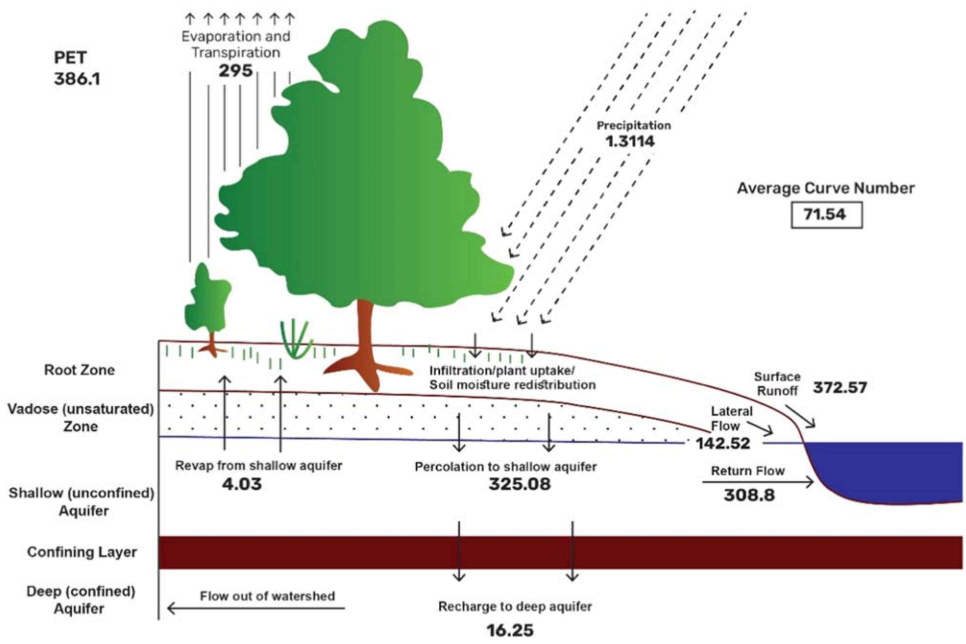

Figure 7. Annual values of the hydrological components of the water balance in mm/year (averaged over 1985–2021).

In terms of water balance, the author obtained a mean monthly evapotranspiration of 24.58 mm, surface runoff of 31.05 mm, and a water yield of 69.99 mm. This study reported that approximately 20% of the precipitation over the watershed returned to the atmosphere as evapotranspiration due to the presence of huge vegetation in the area. However, the surface runoff showed values of 30% of the precipitation recorded in the basin.

3.1.4. Monthly flow pattern

Figure 8 illustrates the analysis of the daily streamflow (Q) for the Upper Humber River. The streamflow values are presented in cubic meters per second (cms). The plot shows key statistics, including the maximum, minimum, mean, and median streamflow, along with the 5th and 95th percentile exceedance levels. The analysis covers each day of the year, from 1985 to 2022, with specific attention to the year 2000. An important observation from figure 8 is the much higher volatility of the red curve (year 2000), which represents the maximum streamflow, compared to the mean and median curves. This could be due to a variety of factors, including seasonal variations, extreme weather events, or changes in land use over time. Such high volatility in the maximum streamflow indicates a significant range in the streamflow values. This could have implications for flood risk management and water resource planning in the UHRW. Further investigation is needed to understand the causes of this high volatility and to develop strategies to manage its potential impacts.

The analysis of the daily streamflow for the Upper Humber River indicates a right-skewed distribution, with the mean curve consistently above the median curve, which is a common characteristic of streamflow distributions (Dethier *et al* 2020). This skewness is attributed to occasional high flow events, particularly during periods of heavy rainfall or rapid snowmelt, which affect the mean more than the median (Zhu *et al* 2016). Interestingly, the difference between the mean and median is larger during low flow months and smaller during high flow months, indicating that extreme events have a more significant impact on the mean during low flow periods (Kempen *et al* 2021). This pattern has implications for water resource management, emphasizing the importance of considering both mean and median values in hydrological analyses. It also underscores the need to understand the factors contributing to their differences, especially in predicting and preparing for extreme events.

Figure 9 shows the unique pattern of the Upper Humber River discharge changes throughout the months and seasons. Every river has its own unique response to weather factors such as precipitation, evaporation, and seasonal changes. Figure 9 also shows the average monthly discharge in Reidville from 1984 to 2022. The lowest discharge was recorded in February, with an average of 29.12 $m^3 s^{-1}$ computed by averaging the mean February discharge from 1984 to 2022. On the other hand, the highest average discharge occurred in May with a value of 247.25 $m^3 s^{-1}$. During the summer season, the highest flow was recorded in June (125.35 $m^3 s^{-1}$) and the lowest in August (39.21 $m^3 s^{-1}$).

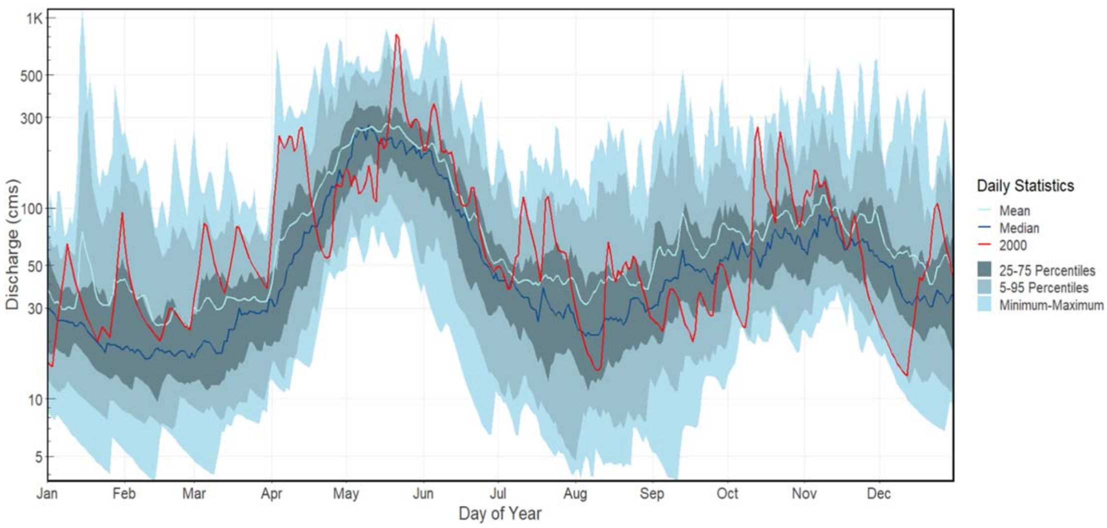

Figure 8. Daily streamflow analysis for the Upper Humber River Watershed, UHRW (water years 1985–2022), with specific focus on the year 2000 (red line). Maximum, minimum, mean, and median streamflow or discharge Q (cms = cubic meters per second, $m^3 s^{-1}$), and 5 and 95% exceedance levels for each day of the year.

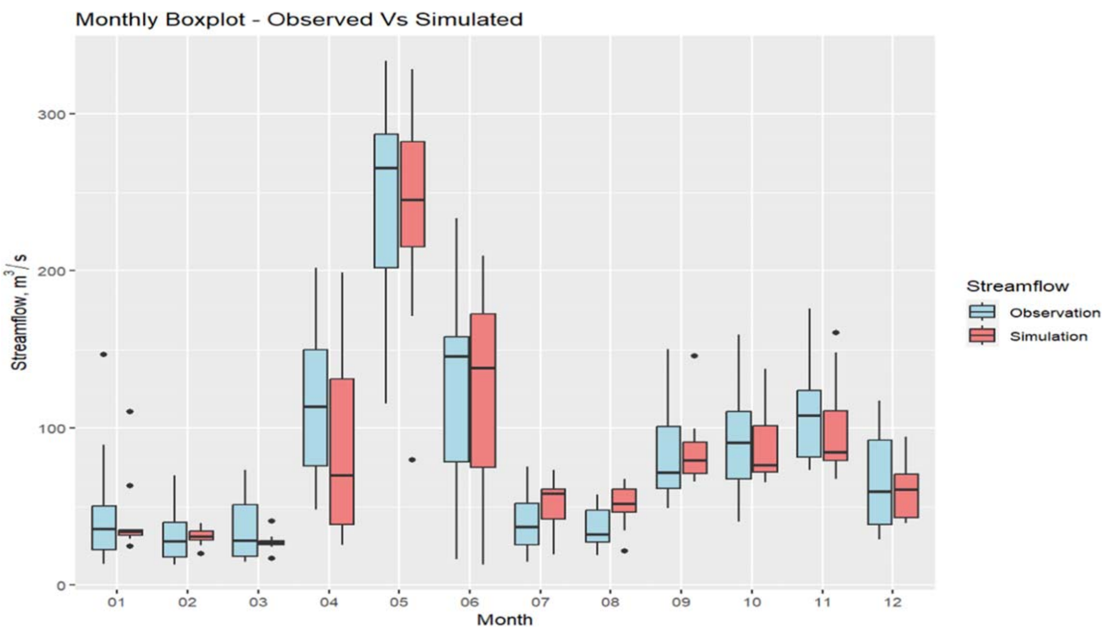

Figure 9. Monthly streamflow boxplot (observed and simulated data) of the Upper Humber River Watershed (UHRW).

The monthly boxplot of streamflow analysis provides valuable insights into the variation of streamflow over the course of a year. Figure 9 highlights the observed and simulated streamflow patterns, enabling a detailed monthly comparison. It is clear from this figure that the observed flow exhibits higher volatility compared to the predicted flow. Examining the average observed and simulated streamflows for each month reveals distinctive hydrological patterns. Notably, the spring and early summer months (April, May, and June) demonstrate the highest average streamflow values, exceeding 240 $m^3 s^{-1}$, with the simulated values closely aligning with the observed trends. This implies a noticeable seasonal peak in water flow, likely influenced by factors such as snowmelt in April and heightened precipitation in May and June. Subsequently, a relatively higher flow is observed during September, October, and November, attributed once again to increased rainfall during these months. Conversely, the winter months (December, January, February, and March) exhibit lower streamflow values, with averages ranging from 30 to 60 $m^3 s^{-1}$, indicating reduced water flow during colder periods. The total observed and simulated streamflows further emphasize these seasonal patterns, with higher cumulative values during the summer and lower totals in the winter.

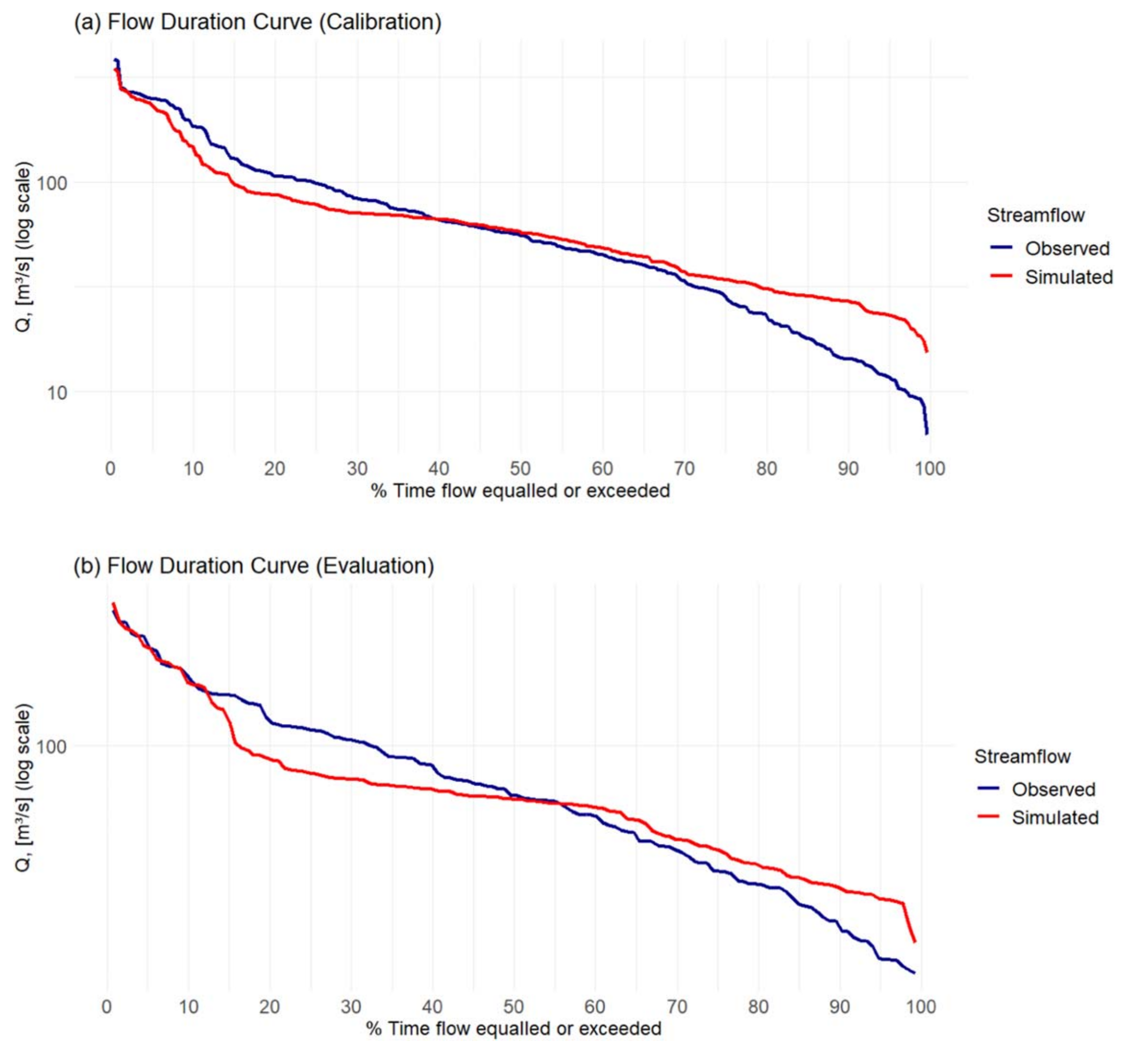

Figure 10. Flow duration curve (FDC) of observed and simulated streamflows at Reidville for (a) calibration and (b) evaluation periods. Here, discharge, Q ($m^3 s^{-1}$ in log scale) and % time flow equalled or exceeded or exceedance probability, P.

3.1.5. Flow duration curve

The FDC generated for the measured and simulated flows is shown in figure 10. According to the graph, the flows were classified as high (1%–15%), medium (16%–60%), and low (61%–100%). Additionally, percentile flows between 16% and 40% are regarded as high-medium flows and 60%–80% as low-medium flows. According to the FDC curve, the SWAT model successfully estimated the extraordinary peak and low flows of the hydrograph. During the recession phase of the FDC, the model was slightly underpredicted.

The FDC provides valuable insights into the river's hydrological characteristics. As observed from the data, the river exhibits a clear inverse relationship between flow rate and the percentage of time (figure 10). The simulated flow rates generally follow the observed trends, indicating a reasonable agreement between the observed and simulated values. We have implemented a logarithmic scale on the discharge (flow rate) axis. This logarithmic scale allows for the effective representation of a wide range of flow values, accommodating the significant variability in river discharge (Searcy 1959, Vogel and Fennessey 1994). In the lower percentiles, the simulated values tend to be slightly higher than the observed ones, while in the higher percentiles, the simulated values show a more pronounced divergence. The FDC curve illustrates the variability in flow rates over time, showcasing the river's dynamic nature, which reflects the influence of local contextual factors such as precipitation, snowmelt, and land use on the river's discharge patterns (Song *et al* 2021). The steep rise in flow rates at lower percentiles suggests quick responses to precipitation events, while the extended, less steep tail at higher percentiles indicates sustained flows during baseflow conditions (figure 10). The FDC for the UHRW, with the incorporation of a logarithmic scale, is a crucial tool for understanding the river's hydrological behavior and informing water resource management strategies in the region.

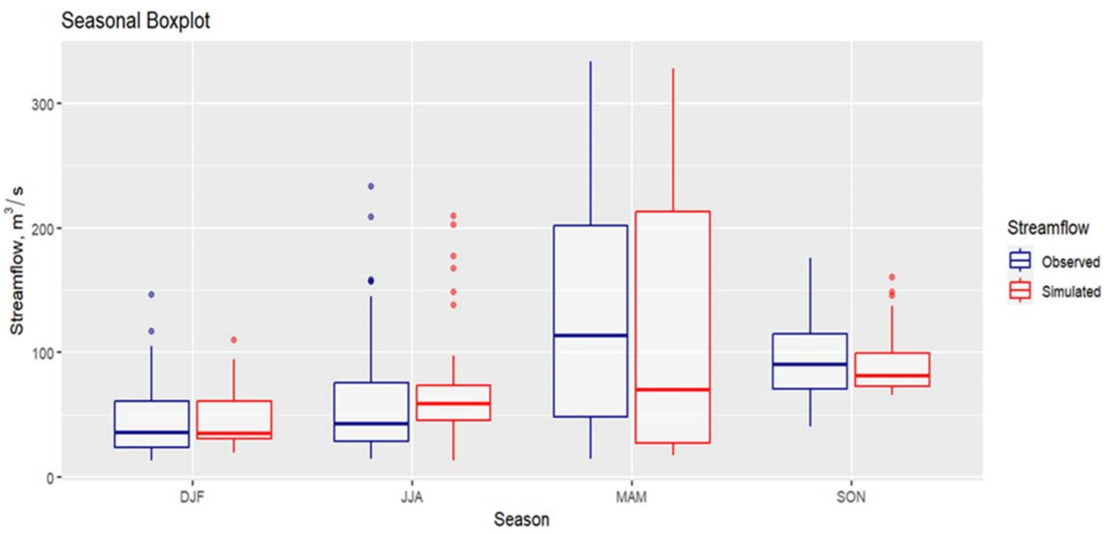

Figure 11. Seasonal box plot. (DJF—December, January, February, JJA- June, July, August, MAM- March, April, May, SON- September, October, November).

Table 7. Model performance based on seasonal data analysis.

Metric	Winter	Summer	Spring	Fall	Annual
NSE	0.65	0.91	0.89	0.79	0.88
R^2	0.68	0.93	0.91	0.84	0.89
PBIAS	−6.00	10.20	−9.90	−5.50	−7.20

4. Seasonal analysis

To understand the performance and accuracy of the SWAT model, it is necessary to conduct a thorough analysis of different aspects of the model output. Therefore, seasonal data analysis was used to understand the model's performance during the seasons. The seasonal boxplot in figure 11 further analyzed the data by grouping them into four seasons: Winter, Summer, Fall, and Spring. These box plots allow for a visual comparison of the distribution of observed and simulated data across different seasons, providing further information about the performance and accuracy of the comparison of the distribution and range of values for each season and a deeper understanding of the seasonal patterns (Lye and Hirschberg 2020). In addition to analyzing seasonal patterns, it is essential to evaluate the performance of the SWAT model. The model performances for each season are listed in table 7. This suggests that considering seasonal variations in the data can lead to more accurate and reliable calibration of the SWAT model. Additionally, the evaluation of the SWAT model using statistical measures, such as R^2, NSE, and PBIAS, provided further insights into its performance and accuracy (Zare *et al* 2022a).

4.1. Model uncertainty

The study utilized the SUFI-2 algorithm for uncertainty analysis, which is a widely used approach for sensitivity analysis, uncertainty assessment, calibration, and validation of hydrological parameters (Arnold *et al* 2012b, Abbaspour *et al* 2018, Abbaspour 2022). The results were expressed using the 95 percent prediction uncertainty (95PPU) and were compared with the observation signals using R^2, NSE, and PBIAS statistics. However, it was noted that the 95PPU results are not generally comparable to the observation with these statistics. Therefore, the study suggested the use of r- and p-factor measurements to address this limitation (Abbaspour 2007). The p-factor, which indicates the percentage of measured data bracketed by 95PPU, was found to be 1, signifying 100% bracketing of the actual data and indicating the correct simulation process. On the other hand, the r-factor, used to measure the calibration quality and specify the thickness of the 95PPU, was found to have a lower value, indicating a lower uncertainty bound of the prediction (Abbaspour *et al* 2018). These findings highlight the importance of using the p- and r-factors to confirm the power of the uncertainty assessment and model calibration in table 6 (Abbaspour 2022).

4.2. Discussion

The main objective of this study was to evaluate the performance of the SWAT model to simulate runoff and water balance components in a Boreal ecozone basin, and the results demonstrated its effectiveness in doing so. This study identified five key parameters that significantly influenced the simulations: the SCS runoff CN, the temperature lapse rate, the effective hydraulic conductivity, the soil evaporation compensation factor, and the plant uptake compensation factor at the HRU level. Interestingly, a separate investigation conducted in Alberta using the same hydrological model found comparable results (Abbaspour *et al* 2010). Similarly, Rufino *et al* (2022) used the SWAT model to simulate stream flows and obtained similar results, with CN2 being the most sensitive parameter. The calibration parameters had a significant impact on the model outcomes.

To improve the accuracy of the hydrograph simulation, the CN2 value was calibrated to be within the range of −20% to 20%. The calibrated CN2 value is 0.0996, indicating a relatively low number of runoff curves. This suggests that the watershed has a high infiltration and low runoff potential. Aawar and Khare (2020) showed that peak flow and discharge may increase because of this calibrated parameter value. The v_CH_K2.rte ranges from 5.0–130.0, and has been fitted to a value of 63.625, which allows water to move through the alluvium more quickly, resulting in a higher streamflow, similar to that observed by Zare *et al* (2022b). The temperature lapse rate (v_TLAPS.sub) is an important factor in the model processes. The range of v_TLAPS.sub was −10 to 10, and it was fitted to a value of 9.86, which resulted in a greater decrease in temperature with altitude, which could affect the simulations of plant growth and evapotranspiration, as discussed by Jiang *et al* (2011).

However, increasing the peak flow during storm events proved to be challenging, because surface runoff occurred throughout the entire period. Reducing ESCO helped increase soil depth and counter water shortages from the lower to upper layers, leading to higher soil evaporation, as observed by Malagò *et al* (2016) and Raihan *et al* (2020). Conversely, the lack of lower sensitivity in EPCO suggests that rainfall was consistently high throughout the study period, similar to that observed by Me *et al* (2015). In contrast to the findings of Ashine and Bedane (2022), who identified EPCO as the most sensitive parameter for highland watersheds, we found that groundwater parameters, namely GWQMN, GW_REVAP, AWC, and EPCO, were highly sensitive. Specifically, we observed that GWQMN and GW_DELAY are crucial for simulating baseflow. The differences in these results could be attributed to the higher forest cover and undulating topography of the study area (Zhang *et al* 2020).

In this study, the hydrological characteristics of various sub-basins in the study area were investigated to understand the water balance and yield. The data revealed significant variations in key parameters across the sub-basins, with sub-basin 12 being the largest (1,392.10 km^2) and sub-basin 26 being the smallest (0.11 km^2). Sub-basin 30 exhibited the highest monthly flow rate of 99 $m^3 s^{-1}$. The SCS CN values ranged from 47.86 to 90.57, reflecting diverse hydrological responses to precipitation and land use characteristics in the region. Similar approaches were used by Ahl *et al* (2008) in a mountainous watershed characterized by its snow-dominant nature in Montana, USA, where they identified the most sensitive parameters, such as snowmelt and soil parameters.

Surface runoff, deep percolation, and ET were identified as the dominant sources of water yield in the UHRW, contributing approximately 28, 25, and 23% of the total water yield, respectively. Similar significant surface runoff findings were reported in other Boreal region basins by Devito *et al* (2005) in a Canadian aspen-forested headwater catchment, and by Fu *et al* (2014) and Watson *et al* (2008) in the Shield Basin, Canada, using the SWAT model. These studies also observed a significant influence of evaporation and transpiration processes on water flows, owing to the presence of vegetation. Sub-basins 21 and 29 showed the highest annual ET at 376 mm, whereas basin 11 exhibited the lowest ET at 109 mm. Overall, the ET of the basin accounted for 23% of the total water balance. Considering the steep slopes and high preservation level of the UHRW, it is likely that evaporation and transpiration processes predominate over runoff, further influencing the sensitivity of the identified parameters, as suggested by Liang *et al* (2020).

The results of the model performance evaluation demonstrated an excellent agreement between the simulated and observed flows, as shown in figure 5. This agreement is further supported by the statistical analyses presented in table 6, which utilized the metrics proposed by Abbaspour *et al* (2010) for large basin calibration and the statistical metrics suggested by Moriasi *et al* (2007). These positive findings align with those of similar studies conducted by Liang *et al* (2020) in the Wilmot River Watershed, an agricultural watershed in west-central Prince Edward Island, Atlantic Canada, where SWAT effectively modeled water availability, hydrological regime, land use, and land cover impacts, yielding favorable statistical results.

Rufino *et al* (2022) employed the SWAT model in a data-scarce basin in Brazil. Despite the scarcity of data in this basin, the SWAT model efficiently generated flow data, thereby demonstrating its adaptability to data-limited settings. Similarly, Fu *et al* (2015) utilized SWAT to investigate the uncertainty arising from the model structure and parameters in a Canadian Shield catchment located in Ontario, Canada. The study demonstrated strong agreement between the simulated and observed flows, particularly with respect to seasonality. These findings highlight the reliable performance of the SWAT model in various hydrological and geographical settings, reflecting its versatility and potential for accurate streamflow simulations in various environments.

This discussion highlights the significant impact of methodological choices, including data selection, calibration parameters selection, and choice of objective function, on the study's results. Notably, the model efficiently simulated the water flow in the study area compared with a single gauging station in the UHRW. The successful approach used in this study can be attributed to the absence of missing weather data in the UHRW, as indicated by Tan *et al* (2019). The availability of complete data greatly contributed to the overall success of this study. The challenges discussed in this study underscore the crucial role of hydrological modeling in the Kelantan River Basin (KRB) and similar watersheds, emphasizing the importance of accurate and reliable hydrological assessments in these regions. Such assessments are essential for effective water resource management and informed decision-making in the face of changing environmental conditions, and the challenges of achieving socio-economic sustainability.

The FDC analysis demonstrated that the SWAT model successfully estimated both the extraordinary peak flows and low flows of the hydrography, demonstrating its capability to capture extreme events and baseflow conditions. However, the model slightly under-predicted the flow values during the recession phase of the FDC. This underprediction highlights the need for further investigation and fine-tuning of the model to improve its performance in accurately simulating baseflow conditions. FDCs provide valuable insights into the frequency and magnitude of flows, making them essential for climate change impacts, water resource management, environmental planning, and flood control efforts (Vogel and Fennessey 1994, Daraio 2017, Fujita *et al* 2022). The successful estimation of peak and low flows in the UHRW using the SWAT model reaffirms its ability to represent the hydrological dynamics of the region effectively. Therefore, targeted improvements should be made to enhance the accuracy of the model during a recession. Overall, the performance of the SWAT model in estimating the flow duration in the UHRW demonstrated its potential for supporting water management decisions and understanding the hydrological cycle behavior of the region.

The statistical metrics presented in table 7 were used to evaluate the model performance across different seasons. These metrics provide insight into how well the model predictions match the observed data for various periods. The NSE values for all seasons and annual periods were positive and ranged from 0.65 to 0.91. According to Nash and Sutcliffe (1970), a positive NSE value indicates that the model's predictions are generally consistent with observed data. Higher NSE values (closer to 1) imply a better fit of the model to the observed data. The NSE values in this evaluation suggested that the model performed reasonably well across all seasons and annually (Moriasi *et al* 2007, Abbaspour *et al* 2018). The relatively low NSE value for winter (0.65) may indicate room for improvement in capturing hydrological processes during this season (Arnold *et al* 2012a, McMillan *et al* 2016, Liu 2020). The R^2 values range from 0.68 to 0.93, indicating a strong correlation between the model predictions and the observed data for all seasons and the annual period. These high R^2 values imply that the model explains a significant portion of the variability in the observed data, which is a positive sign of the model's performance (Krause *et al* 2005, Arnold *et al* 2012b). The PBIAS values ranged from −5.50% to 10.20%, indicating some degree of bias in the model's predictions compared with the observed data (Abbaspour *et al* 2018). The PBIAS values are relatively low, suggesting that the model predictions are generally close to the observed values in terms of magnitude. The overall PBIAS value for all seasons and the annual period was −7.20%, implying a slight underestimation bias in the model's predictions, on average. Finally, statistical evaluation suggests that the model exhibits reasonable performance across different seasons and annually.

The UHRW is a Boreal ecozone watershed characterized by mountains, dense forests, cold climates, and significant snowfall, all of which play crucial roles in regulating the hydrological cycle. Processes, such as precipitation, ET, groundwater flow, and streamflow, are intricately linked within these catchments. In our study, we applied the SWAT model, which has proven to be an invaluable resource for describing the hydrology of the UHRW. From an operational standpoint, it is essential for hydrological models to transparently present their limitations so that researchers and managers are well-informed about their usefulness and capabilities when using this tool. This model has the potential to address a wide range of inquiries such as assessing infrastructure development projects, exploring land cover substitutions, studying agricultural impacts, and predicting shifts in hydrological and meteorological conditions. Furthermore, the integration of simulations with crop yield, nutrients, sediment, and water quality modeling can be valuable, especially when considering climate change and agricultural sustainability, given the high complexity of the SWAT model. Using this versatile model, we can gain valuable insights into the dynamics of the UHRW and make informed decisions to ensure sustainable water resource management and ecological preservation in Boreal ecozone catchments.

5. Conclusion

This study presents hydrological characteristics of the Upper Humber River Watershed (UHRW) located in western Newfoundland, Canada, using the Soil and Water Assessment Tool (SWAT) model. Considering the topographical features, vegetation distribution, soil composition, and climatic variability within the UHRW, this study emphasizes the utilization of a model-based approach to address the challenges associated with effective watershed management. Through calibration (1984–2010) and evaluation (2011–2022), the SWAT model captured the complex hydrography of the UHRW, achieving a reasonable match between the simulated and observed streamflow data.

To unravel the hydrological processes within the UHRW, this study explored the vital components of the watershed water balance. These include evapotranspiration, surface runoff, and deep percolation, all of which contribute significantly to the overall water yield. Notably, the prevalence of surface runoff during the plant growing season and the pronounced impact of precipitation and temperature variations on water yield emphasize the sensitivity of hydrological processes to climate fluctuations. This study highlights the potential of the SWAT model as a tool for understanding the hydrology of the UHRW. The calibrated model not only allows the assessment of climate change effects on water resources but also can inform sustainable practices in the agricultural and forestry domains. The importance of these findings extends to hydrological modelers, researchers, water resources engineers, and decision-makers involved in watershed management, including watershed users interested in the quality of watershed water flow. This study effectively leveraged the SWAT model to uncover the nuanced hydrological processes occurring within the UHRW, however it also highlighted that more research is needed in the UHRW to understand for instance how the streamflow behaves under various stressors, including agricultural runoff, forest clear-cutting or industrial infrastructure building, or what are the needed quality parameters for the streamflow to protect the aquatic life naturally occurring in it, and to provide essential water resources for watershed inhabitants and users. This study provides a foundation for informed water resource management in this region by shedding light on essential hydrological processes and their potential responses to various changes. The insights gained not only contribute to the understanding of Boreal areas watershed behavior but also offer invaluable guidance for future research and sustainable water management strategies.

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Data availability statement

All data that support the findings of this study are included within the article.

Ethical compliance

This research did not involve any participation by humans or animals.

Conflict of interest statement

The authors declare that they have no affiliations with or involvement in any organization or entity with financial interest in the subject matter or materials discussed in this manuscript.

Author contributions

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References

AAFC 2020 URL https://agriculture.canada.ca/en/environment/climate-scenarios-agriculture

Aawar T and Khare D 2020 Assessment of climate change impacts on streamflow through hydrological model using SWAT model: a case study of Afghanistan *Model. Earth Syst. Environ.* **6** 1427–37

Abbaspour K C 2007 User manual for SWAT-CUP, SWAT calibration and uncertainty analysis programs *Swiss Federal Institute of Aquatic Science and Technology* (Eawag) 93

Abbaspour K C 2015 SWAT-CUP: SWAT calibration and uncertainty programs—a user manual (Eawag) 16–70

Abbaspour K C, Faramarzi M, Rouholahnejad E *et al* 2010 *Hydrological Modeling of Alberta Using Swat Model* Alberta Water Research Institute 1–83 https://albertawater.com

Abbaspour K C 2022 The fallacy in the use of the 'best-fit' solution in hydrologic modeling *Sci. Total Environ.* **802** 149713

Abbaspour K C, Johnson C A and Van Genuchten M T 2004 Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure *Vadose Zone J.* **3** 1340–52

Abbaspour K C, Vaghefi S A and Srinivasan R 2018 A guideline for successful calibration and uncertainty analysis for soil and water assessment: a review of papers from the 2016 international SWAT conference *Water* **10** 6

Ahl R S, Woods S W and Zuuring H R 2008 Hydrologic Calibration and Validation of SWAT in a Snow-Dominated Rocky Mountain Watershed, Montana, U.S.A. *JAWRA Journal of the American Water Resources Association* **44** 1411–30

Akoko G, Le T H, Gomi T and Kato T 2021 A review of SWAT model application in Africa *Water* **13** 1313

Allen R, Pereira L S, Raes D and Smith M 1998 https://fao.org/3/x0490e/x0490e06.htm (accessed 3.1.23).

Altdorff D, Galagedara L and Unc A 2017 Impact of projected land conversion on water balance of boreal soils in western Newfoundland *Journal of Water and Climate Change* **8** 613–26

Amichev B Y, Bentham M J, Cerkowniak D, Kort J, Kulshreshtha S, Laroque C P, Piwowar J M and Van Rees K C J 2015 Mapping and quantification of planted tree and shrub shelterbelts in Saskatchewan, Canada *Agroforest Syst.* **89** 49–65

Amponsah A O, Daraio J A and Khan A A 2019 Implications of climatic variations in temporal precipitation patterns for the development of design storms in Newfoundland and Labrador *Can. J. Civ. Eng.* **46** 1128–41

Arnold J G, Moriasi D N, Gassman P W, Abbaspour K C, White M J, Srinivasan R, Santhi C, Harmel R D, Van Griensven A and Van Liew M W 2012a SWAT: model use, Calibration, and validation *Trans. ASABE* **55** 1491–508

Arnold J G, Moriasi D N, Gassman P W, Abbaspour K C, White M J, Srinivasan R, Santhi C, Harmel R D, Van Griensven A and Van Liew M W 2012b SWAT: Model use, calibration, and validation *Trans. ASABE* **55** 1491–508

Ashine E T and Bedane M T 2022 Most sensitive parameters of soil and water assessment Tool (SWAT) hydrological model: a review *Advances in Oceanography* **3** 1–6 AOMB.MS.ID.000558.

Atkisson E J 1915 Procedure in the investigation of a proposed water power development. professional memoirs *Corps of Engineers, United States Army, and Engineer Department at Large* **7** 123–44

Baehre R, Luther J, Hearn B, Novakowski N, Piercey D, Strickland D, Lier O, Gill P and Bowers W 2011 Sustainability in the Humber River Basin *Int. J. of Global Warming* **3** 3–29

Behera P K and Devi T T 2022 Study on impact of urbanization by SWAT model in Iril River, Northeast India *Hydrological Modeling* (Springer) 385–93

Bera S and Maiti R 2021 Assessment of water availability with SWAT model: a study on Ganga River *J. Geol. Soc. India* **97** 781–8

Beven K 2019 How to make advances in hydrological modelling *Hydrol. Res.* **50** 1481–94

Brandt J, Flannigan M, Maynard D, Thompson I D and Volney W J A 2013 An introduction to Canada's boreal zone: ecosystem processes, health, sustainability, and environmental issues introduction *Environmental Reviews* **21** 207–26

Brighenti T M, Bonumá N B, Srinivasan R and Chaffe P L B 2019 Simulating sub-daily hydrological process with SWAT: a review *Hydrol. Sci. J.* **64** 1415–23

Buakhao W and Kangrang A 2016 DEM resolution impact on the estimation of the physical characteristics of watersheds by using SWAT *Advances in Civil Engineering* **2016** 1–9

Burt T P and Heathwaite A L 1996 The hydrology of the siapton catchments *Field Studies* **8** 543–57 http://www.field-studies-council.org/fieldstudies/documents/vol8.4_243.pdf

Chathuranika I M, Gunathilake M B, Baddewela P K, Sachinthanie E, Babel M S, Shrestha S, Jha M K and Rathnayake U S 2022 Comparison of two hydrological models, HEC-HMS and SWAT in runoff estimation: application to huai bang sai tropical watershed, Thailand *Fluids* **7** 267

Chowdhury H-U A 2019 *Hydrologic Modelling of Humber River Basin (Master thesis). Memorial University of Newfoundland, St. John's, Newfoundland*

Cordeiro M R, Lelyk G, Kröbel R, Legesse G, Faramarzi M, Masud M B and McAllister T 2018 Deriving a dataset for agriculturally relevant soils from the soil landscapes of Canada (SLC) database for use in soil and water assessment tool (SWAT) simulations *Earth System Science Data* **10** 1673–86

Daggupati P, Shukla R, Mekonnen B, Rudra R, Biswas A, Goel P K, Prasher S and Yang W 2018 Hydrological responses to various land use, soil and weather inputs in Northern Lake Erie Basin in Canada *Water* **10** 222

Daraio J A 2017 Potential climate change impacts on streamflow and recharge in two watersheds on the New Jersey coastal plain *J. Hydrol. Eng.* **22** 05017002

Daraio J A 2020 Hydrologic model evaluation and assessment of projected climate change impacts using bias-corrected stream flows *Water* **12** 2312

Dethier E N, Sartain S L, Renshaw C E and Magilligan F J 2020 Spatially coherent regional changes in seasonal extreme streamflow events in the United States and Canada since 1950 *Sci. Adv.* **6** eaba5939

Devia G K, Ganasri B P and Dwarakish G S 2015 A review on hydrological models. aquatic procedia *International Conference On Water Resources, Coastal And Ocean Engineering (Icwrcoe'15)* **4** 1001–7

Devito K J, Creed I F and Fraser C J D 2005 Controls on runoff from a partially harvested aspen-forested headwater catchment, Boreal Plain, Canada *Hydrological Processes* **19** 3–25

Dwarakish G S and Ganasri B P 2015 Impact of land use change on hydrological systems: A review of current modeling approaches *Cogent Geoscience* **1** 1115691

ECC 2023a https://gov.nl.ca/ecc/waterres/flooding/humber/ (accessed 1.24.23).
ECC 2023b https://gov.nl.ca/ecc/waterres/flooding/humber/ (accessed 4.6.23).
Esri 2023 *Esri Land Cover [WWW Document].* https://livingatlas.arcgis.com/landcover (accessed 4.6.23)
FFA 2022 *Interesting Facts About Our Agriculture Industry [WWW Document]. Newfoundland and Labrador Farm Guide.* https://gov.nl.ca/farm-guide/interesting-facts-about-our-agriculture-industry/ (accessed 2.1.23)
Frankenberger J R and Daneshvar F 2019 (accessed 1.23.23).
Fujita T *et al* 2022 Simulating discharge in a non-dammed River of Southeastern South America using SWAT model *Water* **14** 488
Fu C, James A L and Yao H 2014 SWAT-CS: Revision and testing of SWAT for Canadian Shield catchments *Journal of Hydrology* **511** 719–35
Fu Congsheng, James April L. and Yao Huaxia 2015 Investigations of uncertainty in SWAT hydrologic simulations: a case study of a Canadian Shield catchment *Hydrological Processes* **29** 4000–17
Gassman P W, Sadeghi A M and Srinivasan R 2014 Applications of the SWAT model special section: overview and insights *J. Environ. Qual.* **43** 1–8
Getu Engida T, Nigussie T A, Aneseyee A B and Barnabas J 2021 Land use/land cover change impact on hydrological process in the upper baro Basin, Ethiopia *Applied and Environmental Soil Science* **2021** e6617541
Gupta H V, Sorooshian S and Yapo P O 1999 Status of automatic calibration for hydrologic models: comparison with multilevel expert calibration *J. Hydrol. Eng.* **4** 135–43
Hassan D 2020 Newfoundland and labrador hurricane season outlook 2020 *NL Water Resources Management Division* **1** 18
Howell T A and Evett S 2017 *The Penman-Monteith Method. USDA-ARS, Southern Plains Area, Conservation & Production Research Laboratory.*
Ireson A M *et al* 2015 The changing water cycle: the Boreal Plains ecozone of Western Canada *WIREs Water* **2** 505–21
Jasim F 2014 *Basin (NL) and Selection of an Appropriate Model Forcing Dataset (Master thesis). Memorial University of Newfoundland, St. John's, Newfoundland.*
Jiang R, Li Y, Wang Q, Kuramochi K, Hayakawa A, Woli K and Hatano R 2011 Modeling the water balance processes for understanding the components of River discharge in a non-conservative watershed *Transactions of the ASABE (American Society of Agricultural and Biological Engineers)* **54** 2171–80
Kempen G, van der Wiel K and Melsen L A 2021 The impact of hydrological model structure on the simulation of extreme runoff events *Natural Hazards and Earth System Sciences* **21** 961–76
King M, Altdorff D, Li P, Galagedara L, Holden J and Unc A 2018 Northward shift of the agricultural climate zone under 21st-century global climate change *Sci. Rep.* **8** 7904
Krause P, Boyle D P and Bäse F 2005 Comparison of different efficiency criteria for hydrological model assessment *Advances in Geosciences* **5** 89–97
Krysanova V and White M 2015 Advances in water resources assessment with SWAT—an overview *Hydrol. Sci. J.* **60** 771–83
Liang K, Jiang Y, Qi J, Fuller K, Nyiraneza J and Meng F 2020 Characterizing the impacts of land use on nitrate load and water yield in an agricultural watershed in Atlantic Canada *Science of The Total Environment* **729** 138793
Liu D 2020 A rational performance criterion for hydrological model *J. Hydrol.* **590** 125488
Liu J, Liu T, Bao A, De Maeyer P, Feng X, Miller S N and Chen X 2016 Assessment of different modelling studies on the spatial hydrological processes in an arid alpine catchment *Water Resour. Manage.* **30** 1757–70
Lye J and Hirschberg J G 2020 (https://doi.org/10.13140/RG.2.2.15464.83203)
Malagò A, Efstathiou D, Bouraoui F, Nikolaidis N P, Franchini M, Bidoglio G and Kritsotakis M 2016 Regional scale hydrologic modeling of a karst-dominant geomorphology: The case study of the Island of Crete *Journal of Hydrology* **540** 64–81
Me W., Abell J. M. and Hamilton D. P. 2015 Effects of hydrologic conditions on SWAT model performance and parameter sensitivity for a small, mixed land use catchment in New Zealand *Hydrology and Earth System Sciences* **19** 4127–47
McMillan H 2020 Linking hydrologic signatures to hydrologic processes: a review *Hydrol. Processes* **34** 1393–409
McMillan H K, Booker D J and Cattoen C 2016 Validation of a national hydrological model *J. Hydrol.* **541** 800–15
MIR 2018 *Trophy salmon fishing on the Humber River Western Newfoundland [WWW Document]. Explore Newfoundland with Marble Inn & Suites.* https://explorenewfoundland.com/trophy-salmon-on-the-humber (accessed 1.15.23).
Mishra S K and Singh V P 2003 SCS-CN method *Conservation Service Curve Number (SCS-CN) Methodology, Water Science and Technology Library.* (*Soil*) ed S K Mishra and V P Singh (Springer Netherlands) 84–146
Moriasi D N, Arnold J G, Van Liew M W, Bingner R L, Harmel R D and Veith T L 2007 Model evaluation guidelines for systematic quantification of accuracy in watershed simulations *Trans. ASABE* **50** 885–900
Muhammad A, Evenson G R, Unduche F and Stadnyk T A 2020 Climate change impacts on reservoir inflow in the prairie pothole region: a watershed model analysis *Water* **12** 271
Nash J E and Sutcliffe J V 1970 River flow forecasting through conceptual models I- a discussion of principles **10** 282–90
Nechifor V and Winning M 2018 Global economic and food security impacts of demand-driven water scarcity—alternative water management options for a thirsty world *Water* **10** 1442
Neitsch S L, Arnold J G, Kiniry J R and Williams J R 2011 *Soil and Water Assessment Tool Theoretical Documentation Version 2009.* Texas Water Resources Institute. 1–647 https://hdl.handle.net/1969.1/128050
Philip S, Sparrow S, Kew S F, Van Der Wiel K, Wanders N, Singh R, Hassan A, Mohammed K, Javid H and Haustein K 2019 Attributing the 2017 Bangladesh floods from meteorological and hydrological perspectives *Hydrol. Earth Syst. Sci.* **23** 1409–29
Posit Team 2023 *RStudio: Integrated Development Environment for R. Posit Software, PBC, Boston, MA.* URL http://posit.co/
R Core Team 2023 _ *R: A Language and Environment for Statistical Computing_. R Foundation for Statistical Computing* https://www.R-project.org/
Raihan F, Beaumont L J, Maina J, Saiful Islam A and Harrison S P 2020 Simulating streamflow in the upper halda basin of southeastern Bangladesh using SWAT model *Hydrol. Sci. J.* **65** 138–51
Rashid I O 2014 Evaluation of SWAT model applicability in a first-order agricultural watershed in southern Ontario (GeographyandEnvironmentalStudiesThesesandDissertations). Wilfrid Laurier University *Geography and Environmental Studies The Sesand Dissertations.*
Reddy A S and Reddy M J 2015 Evaluating the influence of spatial resolutions of DEM on watershed runoff and sediment yield using SWAT *J. Earth Syst. Sci.* **124** 1517–29
Rufino P R, Gücker B, Faramarzi M, Boëchat I G, Cardozo F, Santos P R, Zanin G D, Mataveli G and Pereira G 2022 Evaluation of the SWAT Model for the Simulation of Flow and Water Balance Based on Orbital Data in a Poorly Monitored Basin in the Brazilian Amazon *Geographies* **3** 1–18

Samimi M, Mirchi A, Moriasi D, Ahn S, Alian S, Taghvaeian S and Sheng Z 2020 Modeling arid/semi-arid irrigated agricultural watersheds with SWAT: Applications, challenges, and solution strategies *J. Hydrol.* **590** 125418

Saunders L J, Russell R A and Crabb D P 2012 The coefficient of determination: what determines a useful R2 statistic? *Invest. Ophthalmol. Vis. Sci.* **53** 6830

Schuch G, Serrao-Neumann S, Morgan E and Low Choy D 2017 Water in the city: Green open spaces, land use planning and flood management—an Australian case study *Land Use Policy* **63** 539–50

Searcy J K 1959 (https://doi.org/10.3133/wsp1542A)

Shrestha N K, Du X and Wang J 2017 Assessing climate change impacts on fresh water resources of the Athabasca River Basin, Canada *Sci. Total Environ.* **601** 425–40

Singh L and Saravanan S 2020 Simulation of monthly streamflow using the SWAT model of the Ib River watershed, India | *Elsevier Enhanced Reader.* 10.1016/j.hydres.2020.09.001

SLC 2021 *Soil Landscapes of Canada (SLC) [WWW Document]* URL https://sis.agr.gc.ca/cansis/nsdb/slc/index.html (accessed 4.6.23)

Song C, Wang G, Sun X and Hu Z 2021 River runoff components change variably and respond differently to climate change in the Eurasian Arctic and Qinghai-Tibet Plateau permafrost regions *J. Hydrol.* **601** 126653

Tan M L, Gassman P W, Srinivasan R, Arnold J G and Yang X 2019 A review of SWAT studies in Southeast Asia: applications, challenges and future directions *Water* **11** 914

Unc A, Adamczyk B and Borchard N 2022 Editorial: sustainable and climate-smart agriculture in the boreal and arctic regions *Front. Sustain. Food Syst.* **6** 816726

Vogel R M and Fennessey N M 1994 Flow-duration curves. I: new interpretation and confidence intervals *J. Water Resour. Plann. Manage.* **120** 485–504

Waseem M, Mani N, Andiego G and Usman M 2017 *A Review of Criteria of Fit for Hydrological Models*

Watson B M, McKeown R A, Putz G and MacDonald J D 2008 Modification of SWAT for modelling streamflow from forested watersheds on the Canadian Boreal Plain *Journal of Environmental Engineering and Science* **7** 145–59

Wells J V, Dawson N, Culver N, Reid F A and Morgan Siegers S 2020 The state of conservation in North America's boreal forest: issues and opportunities *Frontiers in Forests and Global Change* **3** 1–18

Wickham H 2016 *ggplot2, Use R!* (Springer International Publishing) 10.1007/978-3-319-24277-4

Wickham H *et al* 2019 Welcome to the tidyverse *Journal of Open Source Software* **4** 1686

Yang J, Reichert P, Abbaspour K C, Xia J and Yang H 2008 Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China *J. Hydrol.* **358** 1–23

Yesuf H M, Melesse A M, Zeleke G and Alamirew T 2016 Streamflow prediction uncertainty analysis and verification of SWAT model in a tropical watershed *Environ. Earth. Sci.* **75** 806

Zambrano-Bigiarini M 2022a *Time Series Management, Analysis and Interpolation for Hydrological Modelling.*

Zambrano-Bigiarini M 2022b *Goodness-of-Fit Functions for Comparison of Simulated and Observed Hydrological Time Series.*

Zare M, Azam S and Sauchyn D 2022a A modified SWAT model to simulate soil water content and soil temperature in cold regions: a case study of the south saskatchewan river basin in Canada *Sustainability* **14** 10804

Zare M, Azam S and Sauchyn D 2022b Evaluation of soil water content using SWAT for southern saskatchewan, Canada *Water* **14** 249

Zhang P, Liu R, Bao Y, Wang J, Yu W and Shen Z 2014 Uncertainty of SWAT model at different DEM resolutions in a large mountainous watershed *Water Res.* **53** 132–44

Zhang H, Wang B, Liu D L, Zhang M, Leslie L M and Yu Q 2020 Using an improved SWAT model to simulate hydrological responses to land use change: A case study of a catchment in tropical Australia *Journal of Hydrology* **585** 124822

Zhu Q, Xuan W, Liu L and Xu Y 2016 Evaluation and hydrological application of precipitation estimates derived from PERSIANN-CDR, TRMM 3B42V7, and NCEP-CFSR over humid regions in China *Hydrol. Processes* **30** 3061–83